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ORIGINAL RESEARCH

Signature identification and verification techniques: state-of-the-art work

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Abstract
Signature identification and verification are some of the biometric systems used for personal identification. Signatures can be considered as authentication of an individual by the analysis of handwriting style, subjected to inter-personal and intra-personal variations. This paper presents an extensive systematic overview of online and offline signature identification and verification techniques. In offline signature verification, surveys related to two approaches, namely, writer-dependent, and writer-independent approaches are presented. Moreover, the compiled study of feature extraction and classification techniques used for signature identification and verification process has also been incorporated. Several databases introduced in the literature are considered to evaluate different signature identification and verification techniques and corresponding results are reported in this article. The entire survey is further summarized in the form of a table for comparisons. In order to reveal the superiority of the present survey, the comparison of the present survey with the existing recent survey works has also been presented. Finally, future directions are provided for further research.

Keywords Signature identification · Signature verification · Handwritten signature · Biometric

1 Introduction

Biometric identification is a method of identifying a person based on physiological and behavioral attributes. The physiological attributes represent the biological characteristics of a person, i.e., the characteristics that a person owns and include fingerprint, hand, iris, DNA, and facial features. Behavioral attributes represent the behavior of a person and it includes voice, signature, dynamics, etc. Biometric systems provide a high level of accuracy as compared to traditional security systems which rely on passwords, personal identification numbers (PINs), or smart cards. This higher accuracy is because biometric attributes of an individual are unique and thus are not easily transferable and cannot be lost, stolen, or broken. Biometric recognition finds its applications in our daily life documents and activities including driving licenses, passport, immigration, voter registration, security applications, medical records, personal device login, smart-cards, etc. Biometric-based solutions can provide personal data privacy and confidential financial transactions. Among biometric systems, a handwritten signature is one of the most widely used personal attributes considered as legal means of individual authentication in administrative and financial institutions. Signatures of every individual can be defined as a combination of symbols and strokes that is basically an attribute of the individual and represent a style of writing which is unique to himself/herself. A signature is used in identifying a person and the genuineness of a document. Signatures can be acquired in two modes, namely, online, and offline. In online mode, signatures are electronically captured with devices such as a writing pad and stylus attached to a computer. Online mode records dynamic features of signature images like writing speed, angle, number of pen-ups, time taken to put a signature, etc., so it is sometimes called dynamic mode. This information leads to better accuracy as the dynamic features are very difficult to simulate. In the offline mode, signatures are written on paper documents from where they are captured with the help of scanners, cameras, etc. Offline mode analyzes

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the shape-related static features of signature images because the features from the signature images are extracted after these are written on a paper sheet. Thus, it is also known as a static model of acquiring signatures. Signatures can be used for different purposes, including personal identification and verification, document retrieval, etc. As a result, many signature identifications and verification algorithms were developed in the literature. A detailed discussion about these algorithms is provided in the consequent section.

The rest of the paper is organized as follows. In Sect. 2, motivations for readers related to this survey are presented. Section 3 provides a description of the feature extraction and classification techniques used for signature identification and verification. Survey results are presented in Sect. 4. Section 5 demonstrates the comparison of the presented survey with the recent survey works. Finally, Sect. 6 concludes this paper and provides some future directions.

2 Motivations

Traditionally, names, social security numbers, PINs, passwords, and tokens were used to recognize the identity of an individual in different circumstances. However, authorizing someone based on a password or a token is just a proxy for verifying the identity of an individual as a password can be shared or a token can be lost. So, a primary motivation behind using a signature as a biometric on documents is that everyone has a unique way of signing (signature), which is different from others. Moreover, signature authentication finds its applications in many areas including financial transactions, access control, security, etc. So, in this paper, the authors have surveyed the various techniques used for signature identification and verification which proved to be useful in separating genuine signatures from the forged signatures. In this survey, the authors have analyzed several feature and classification techniques that can be employed in several combinations for the spike in signature identification and verification rate. Several databases have been mentioned in this paper with their sources to evaluate the performance of signature identification and verification techniques. Moreover, this survey will be fruitful to all those researchers who have an interest in the signature identification and verification field as this survey is helpful in finding the research gaps in the signature identification and verification domain.

3 Description of feature extraction/selection, classification techniques and distance measures for signature identification and verification

A brief description of various feature extraction techniques, feature selection techniques, classification techniques and distance measures are presented in Tables 1, 2, 3 and 4 respectively.

4 Survey results according to considered classification techniques and distance measures

A lot of work has been done till now in order to develop offline signature verification systems based on computer vision and soft computing techniques. Computer vision is described as automation and integration of a wide range of processes and representations for visual perception. Computer vision is considered as the inverse of computer graphics as computer graphics produce image data from 3D models, whereas computer vision often produces 3D models from the image data. Soft Computing refers to a collection of numerous techniques which utilize the human mind to formalize cognitive processes. It deals with imprecision, uncertainty, partial truth, and approximation to attain practicability, robustness, and low solution costs. There are soft computing techniques such as Fuzzy Logic, Artificial Neural Network on which a lot of work has been considered in the literature. In this section, we have provided the literature related to signature identification and verification. A few surveys have been presented in the literature. In the following subsections, a survey of signature recognition and verification based on classification techniques followed by results and discussion is presented.

4.1 Nearest neighbor (NN)

Pal et al. (2016) evaluated the offline signature verification method using texture features on a large Indic script signature dataset named BHSig260 comprising Bangla and Hindi offline signatures. The proposed approach reported AER (Average Error Rate) of 32.72% separately for LBP (Local Binary Patterns) and ULBP (Uniform Local Binary Patterns) based features by employing the Nearest Neighbor approach as a similarity metric to verify signatures. Based on k-NN, they attained EERs of 24.47% and 33.82% on Hindi and Bangla words, respectively. A writer-independent method for offline signature recognition has been proposed by Rajput and Patil (2017). They have used the Histogram of Oriented

Table 1 Feature extraction techniques for signature identification and verification

Feature extraction technique	Key concept	Pros	Cons	Related study
Discrete cosine transform (DCT)	Considers an image as a sum of sinusoids of different magnitudes and frequencies	Important information about the image is concentrated in a few coefficients of DCT Finds its place in image compression applications Better computational efficiency as compared to Discrete Fourier Transform (DFT)	Yields real-valued output whereas the input received from pre-processed block is integer. Hence quantization step is required to generate integer-valued output	Rashidi et al. (2012); Chadha et al. (2013); Liu et al. (2015); Prathibaet al. (2017); Suman et al. (2018)
Local features	Represent the key points in an image such as a point, edge or small image patch	Indicates the texture in image patch Invariant to scale, rotation etc Also called local descriptors Examples: SIFT, SURF, LBP, BRISK, MSER and FREAK Finds applications in image registration, object recognition, image and video classification, action recognition, robot navigation	Necessitate distinguishing interest points No spatial information	Kiskuet al. (2009); Malik et al. (2013); Al-Maqalehet al. (2015); Kurnaz and Al-Khdhairi (2018); Sharif et al. (2018)
Global features	Represent an image as a whole and comprises contour representation, shape descriptors and texture features. These are also known as global descriptors	Good with respect to object recognition, image retrieval, etc Examples: Shape Matrices, Invariant Moments (Hu, Zernike), Histogram of Oriented Gradients (HOG) and Co-HOG Used for image retrieval, object detection and Classification	Gets affected by clutter and partial occlusion Inappropriate to localize objects spatially	Al-Mayyanet al. (2011); Malik et al. (2011); Khan and Dhole (2014); Pawar (2015); Manjunathaet al. (2016); Zalasińskiet al. (2016a); Sharif et al. (2018); Zalasiński and Cpałka (2018b)
Histogram of Oriented Gradient (HOG)	Histograms of directions of gradients (x and y derivatives) are used as features	Utilized for global features extraction Represents both shape and texture Useful in detecting objects in image processing Very accurate for classifying objects	Can generate very large feature vectors resulting in large storage costs Variant to scale and rotation The concluding descriptor vector expands larger thus enlarges the time of feature extraction	Yilmaz et al. (2011); Soleimani et al. (2016a); Rajput and Patil (2017); Taskiran and Cam (2017)
SIFT (Scale-Invariant Feature Transform)	Extracts an image and then transforms it into a large store of local feature vectors	Classic approach Most accurate feature descriptor Invariant to scaling, rotation or translation of image	Based on HOG, hence results in more computational time Not efficient for devices having low power Requires large storage space	Marusicet al. (2015); Nasser and Dogru (2017); Sriwathsanet al. (2020)
Gaussian Mixture Model (GMM)	Probabilistic model which states that all the data points are generated from a mixture of a finite Gaussian distribution that is not having any known parameter	fastest algorithm Useful in object tracking and extracting features of speech data Finds applications in biometric systems Most statistically mature techniques for clustering	Multiple points to each mixture lead to difficult estimation of covariance matrices The algorithm fails in case of large dimensionality of problem	Humm et al. (2006); Jain et al. (2011); Zapata-Zapata et al. (2016); Xia et al. (2018)

Table 1 (continued)

Feature extraction technique	Key concept	Pros	Cons	Related study
Speeded-Up Robust Features (SURF)	Comprises three steps, namely, feature extraction, feature description and feature matching. It detects key-points from distinct areas of given image	Useful in finding similarity between images Faster as compared to SIFT	Suffers from localization errors with respect to space or scale	Pal et al. (2012); Sharma (2014); Nasser and Dogru (2017); Sriwathsanet al. (2020)
Curvelet transform	It is higher dimensional generalization of the Wavelet transform designed to depict images at distinct scales and distinct angles	Multi-scale transform Effectively represent curves contained in the image of the signature Provides better representation as compared to wavelets Widely applied in application areas of pattern recognition and image compression	Sensitive to orientation variation The computational cost is higher than Fast Fourier Transform (FFT)	Guerbaiet al. (2015); Hadjadjiet al. (2017); Mo et al. (2019)
Contourlet Transform (CT)	Two-dimensional extension of the wavelet transforms and accomplished using the Laplacian pyramid (LP) and directional filter banks (DFB)	Comprises basic images with flexible aspect ratios oriented in various directions in multiple scales Usefulin manyapplications like writer identification, facerecognition, palm print recognition, speech recognition, signature verification	Not suitable for image coding due to redundant transform	Fakhlaiet al. (2009) Pourshahabiet al. (2009); Soleymanpouret al. (2010);Hamadene and Chibani (2016)
Morphological features	Processes digital images based on shape and the basic mathematical morphological operations are dilation, erosion, opening, closing and morphological reconstruction	Mathematical morphological operations extract the relevant shape features while discarding the irrelevant features	The integration of dilation and erosion operations can generate more complicated sequences	Kekreet al. (2010); Pandey and Shantaiya (2012)
Gradient, Structural and Concavity (GSC) features	Gradient features consider local features of image on a small scale; Structural features consider the gradient features at longer distance; and Concavity features detect stroke relationships across the image	The resulted features are efficient in writer identification and verification	As it only works with binarized images, so it is expected that the suitable algorithm (Otsu 1979) has been used to threshold an image	Kaleraet al. (2004); Shaikh et al. (2018)
Gabor wavelet	Acquired by multiplying a sinusoid function with a Gaussian function in the time domain	Two-dimensional Gabor wavelet transform is employed in image processing Operates like local edge detector	Restricted by direction of the edge which is associated to rotation angle; and width of edge which is associated with wavelength	Ling et al. (2010); Sigariet al. (2011); Bagul and Ragha(2014); Shrivastava et al. (2016)

Table 2 Feature selection techniques for signature identification and verification

Feature selection technique	Key concept	Pros	Cons	Related study
Principal Component Analysis (PCA)	Dimensionality reduction method to select the most significant features from the original feature set	Less memory requirements owing to use of a smaller number of uncorrelated variables called principal components Minimizes overfitting Enhances model performance Applications in area of signature recognition and verification, image compression, face recognition, computer graphics	If proper care is not taken, some information may be lost in comparison to original features Standardization of data is essential before applying PCA Principal components turned to be less interpretable as compared to original features	Erkmenet al. (2010); Ismail et al. (2010); Al-Mayyanet al. (2011);Manjunathaet al. (2016);Hadjadjiet al. (2017); Taskiran and Cam (2017); Okawa (2018b)
Linear Discriminant Analysis (LDA)	Method employed to determine a linear combination of features that separates two or more classes of objects	Preferred linear classification approach for more than two classes Simple model Dimensionality reduction approach Supervised classification technique Application areas include image recognition and predictive analytics in marketing Extensions to LDA are: quadratic discriminant analysis (QDA), flexible discriminant analysis (FDA), regularized discriminant analysis (RDA)	Doesn't perform well for few categories' variables Suffers from multicollinearity	Song et al. (2010); Bharathi and Shekar (2014); Manjunathaet al. (2016)
Rough sets	Feature selection technique in order to find a reduced set of features which retains the classification accuracy as original features	Deals with incomplete data Only the facts hidden in data are analyzed Does not require additional information about data Applications in field of machine learning, knowledge discovery and data mining	Unable to handle numerical databases directly Only work with discrete databases	Own et al. (2010); Al-Mayyanet al. (2011); Zhou and Jiang (2011); Das and Roy (2016)

Table 2 (continued)

Feature selection technique	Key concept	Pros	Cons	Related study
Evolutionary computation based feature selection techniques	For feature selection, evolutionary computing methods are used due to its overall optimization capabilities (Xueet al. 2018; Zhang et al. 2018), for example: Particle Swarm Optimization (PSO) (Tian and Gu 2010; Xueet al. 2012; Zhang et al. 2015), Genetic Algorithm (Li et al. 2010; Souza et al. 2011; Aslahi-Shahriet al. 2016), ant colony optimization (Yan and Yuan 2004; O'Boyle et al. 2008) etc	High convergence speed of particle swarm optimization algorithm High exploration ability of genetic algorithm	Most evolutionary computing methods suffer from local optimal stagnation problems (Xueet al. 2014) In many of these methods, there is a lack of the ability to explore and utilize search spaces in a suitable manner (Kohavi and John 1997) Numerous existing evolutionary algorithms comprise only one search strategy and cannot successfully deal with the complex situations that arise in real-world problems	Galballyet al. (2007); Cervanteet al. (2012); Lane et al.(2013); Lane et al. (2014); Malakaret al. (2019); Moslehi and Haeri (2020)

Gradient (HOG) features extraction technique and K-Nearest Neighbor (K-NN) classifier to recognize the signature images. The proposed system is evaluated on a database of offline handwritten signatures which contains 100 signatures in the learning phase and 60 signatures in the testing phase and reported good recognition accuracy.

4.2 Hidden Markov model (HMM)

Fierrezet al. (2007) proposed an on-line signature verification system based on Hidden Markov Model (HMM). The feature extraction is based on seven dynamic time functions, namely, x trajectory, y trajectory, pressure, path tangent angle, path velocity magnitude, log curvature radius, and total acceleration magnitude. Experiments are conducted on MCYT bimodal biometric database. The proposed system achieved 0.74% and 0.05% EER for skilled and random forgeries, respectively. Based on the results of the First International Signature Verification Competition (SVC2004), the proposed system is compared with other state-of-the-art systems.

4.3 Support vector machine (SVM)

Narwadeet al. (2018) developed an offline signature verification scheme based on shape correspondence which employs an adaptive weighted combination of shape context distance and Euclidean distance to recognize the correlation between pixels of different signatures. The calculated distances are then given as an input to the SVM classifier for finding the authenticity of the signature. By evaluating the proposed approach on GPDS synthetic signature database, they achieved an accuracy of 89.58%. To enhance the discriminative ability of the offline signature verification, Okawa (2018b) proposed a new approach by employing Fisher Vector with KAZE features from both foreground and background signature images which were then fused. They considered PCA to reduce the dimensionality of the Fisher Vectors and SVM for the classification of signature images as genuine or forgery. They attained an EER of 5.47% on the MCYT-75 dataset which is better as compared to the ones reported in the state-of-the-art offline signature verification systems (Ferrer et al. 2012; Okawa 2016a, 2016b; Soleimani et al. 2016a). Sharif et al. (2018) demonstrated a framework to verify the offline signatures where global and local features are extracted from the offline signatures. The extracted features are then diminished using the genetic algorithm feature selection approach and the selected features are fed into SVM classifier for verification. The experiments are conducted on three datasets, namely, CEDAR, MCYT, and GPDS synthetic. On the CEDAR dataset, they attained rates of 4.67% (FRR), 4.67% (FAR), and 4.67% (AER) which surpasses the existing offline signature verification approaches

Table 3 Classification techniques for signature identification and verification

Classifier	Key concept	Pros	Cons	Related study
K-Nearest Neighbor (K-NN)	Supervised machine learning algorithm Saves all the available cases and makes classification of new cases based on a similarity measure (e.g., distance functions)	Covers the complete dataset for finding K nearest neighbors There are no assumptions Easy to understand and simple to implement Convenient for multi-class problem Employedfor both classification and regression problems	Sensitive to outliers Not capable to deal with the missing value problem Mathematically expensive due to storage of all training data Requires large memory Requires homogeneous features	Kaleraet al. (2004); Sigariet al. (2011); Abdelrahaman and Abdallah (2013); Boyadzieva and Gluhchev (2014); Zouari et al. (2014); Rajput and Patil (2017); Dorozet al. (2018); Hedjazet al. (2018); Chakravarthi and Chandra (2019)
Hidden Markov Model (HMM)	Sequence classifier Anticipates a succession of hidden (unknown) variables from a set of observed variables	Input of variable length can be handled Powerful statistical base Application areas are data mining, classification, structural analysis, and pattern discovery	Unable to exhibit dependencies between hidden states The Viterbi algorithm used to find relevant succession of hidden states, requires more memory and time Comprises various unstructured parameters	Fierrezet al. (2007); Daramola and Ibiyemi (2010); Tahmasebi and Pourghassem (2013); Zou et al. (2013); Pushpalathaet al. (2014)
MultilayerPerceptron's (MLPs)	Feed forward artificial neural network Employs back propagation to train the network	Deals with incomplete data Application areas are image recognition, machine translation, speech recognition	Requires powerful hardware specifications Difficult to train due to tuning of multiple parameters	Erkmenet al. (2010); Odeh et al. (2011); Kumar et al. (2012); Shekar and Bharathi (2014); Shahi et al. (2017)
Support vector machine (SVM)	Supervised machine learning algorithm Based on finding hyperplane that partitions the dataset into two classes Also known as support vector network (SVN)	Best suited for smaller, cleaner datasets Efficient in spaces having high dimensions Applications include text categorization, image classification, handwriting recognition	Less effective on noisier datasets Inappropriate for large datasets Difficult to select a suitable kernel function Hard to interpret	Guerbaiet al. (2015); Liu et al. (2015); Marusicet al. (2015); Zoiset al. (2016); Bouamraet al. (2018); Narwadeet al. (2018); Okawa (2018b); Sharif et al. (2018); Masoudniaet al. (2019); Zoiset al. (2019a); Vohra and Kedar (2021)
Random forest	Supervised machine learning algorithm An ensemble of decision trees	Highly accurate classifier Parallel in nature Runs efficiently on larger datasets Effectively estimates missing data Ability to balance errors in class population Find applications in classification and regression problems	Complex due to integration of large number of decision trees Classifications generated are difficult to interpret by humans Requires large memory to train various decision trees Slower in predictions	Parodi and Gomez (2014); Shahi et al. (2017); Thenuwara andNagahamulla (2017); Dorozet al. (2018)
Naïve Bayesian (NB) classifier	Supervised classification algorithm Based on applying Bayes' theorem with strong independence presumptions between the attributes (features)	Simple to implement and easy to understand Computationally fast Works well with high dimensions Can also be trained on smaller datasets Insensitive to irrelevant features	Rests on independence assumption i.e. makes a assumption that every-feature is independent Suffers from the issue of 'zero conditional probability' in which the total probability turns to zero for features possessing zero frequency	Barbantan and Potolea (2010); Manjunathaet al. (2016); Thenuwara and Nagahamulla (2017); Chandra (2020)

Table 3 (continued)

Classifier	Key concept	Pros	Cons	Related study
Probabilistic neural network (PNN)	Multi-class classification Feed forward neural network Parent probability distribution function of each class is approximated bya Parzen window and a non-parametric function	Faster and accurate than MLPs Parallel structure Insensitive to outliers Requires a representative training set	Requires more memory space Slower as compared to MLP in case of new cases classification	Meshoul and Batouche(2010); Manjunathaet al. (2016); Porwiket al. (2016); Dorozet al. (2018)
Deep learning	Comprises networks capable of learning unsupervised from data that is unstructured Also known as deep neural learning or deep neural network	Can act as any type of system such as face recognition, image reconstruction, linear or non-linear Does not get affected by computation power High dimensional Can automatically adapt all data Provides higher degree of abstraction Quicker in getting results Can work on large, complex datasets	Difficult to understand Requires high amount of data for training purpose Requires large memory and computing resources More costly Necessitate advanced optimization methods Highly prone to errors	Hafemannet al. (2016); Soleimani et al. (2016a); Hafemannet al. (2017); Hafemannet al. (2018); Hanmandluet al. (2018); Lai and Jin (2019); Melo et al. (2019); Kao and Wen (2020); Poddar et al. (2020); Ghosh (2021a)

Table 4 Distance Measures for signature identification and verification

Distance Measure	Key Concept	Pros	Cons	Related Study
Vector Quantization (VQ)	Maps k-dimensional vectors into a finite set of vectors Each vector is considered a codeword The collection of all code words is called a codebook The representative code word is decided to be closest in Euclidean distance from the input vector	Minimizes search complexity Applications include image and voice compression, voice recognition	Requires large memory Requires more storage space	Faundez-Zanuy (2007); Sharma and Sundaram (2016)
Dynamic Time Warping (DTW)	Computing similarity between two temporal sequences, which may differ in speed Determines all the closest sequences to a test sequence	DTW is averaging of time series which results in more accurate and faster classification Suitable for a smaller number of templates Applicationscomprise speech-word recognition and correlation power analysis	Restricted number of templates Requires actual training samples	Faundez-Zanuy (2007); Shanker and Rajagopalan (2007); Bailadoret al. (2011); Sharma and Sundaram (2016); Song et al. (2016); Xia et al. (2018); Lai and Jin (2019); Parzialeet al. (2019); Riesen and Schmidt (2019)

(Kumar et al. 2012; Bharathi and Shekar 2013; Kumar and Puhan 2014; Guerbaiet al. 2015; Zoiset al. 2016). On the MCYT dataset, they attained rates of 3.67% (FRR), 6.67% (FAR), and 5.0% (AER) which surpasses the existing verification approaches (Alonso-Fernandez et al. 2007; Vargas et al. 2011; Azmi et al. 2016; Soleimani et al. 2016a; Zoiset al. 2016). Whereas the proposed framework attained rates of 4.16% (FRR), 3.33% (FAR), and 3.75% (AER) on the GPDS synthetic dataset which outperforms the state-of-the-art approach (Soleimani et al. 2016a). To provide multi-representational learning for offline signature verification, Masoudniaet al. (2019) analyzed three loss functions for Convolutional Neural Network (CNN), namely, cross-entropy, hinge loss, and Cauchy–Schwarz divergence. Based on the complementary features, these losses were then integrated into dynamic multi-loss functions. The proposed ensemble comprised numerous trials where distinct trials learned different representations for each input based on signature identification job where the multi-representation set was utilized to train the group of SVMs. The experiments were evaluated on three datasets, namely, UT-SIG, MCYT, and GPDS-Synthetic signature datasets, based on writer-independent and writer-dependent approaches to offline signature verification. Based on the writer-dependent approach, the proposed system attained 6.17% EER on the UT-SIG dataset which is better as compared to the best EER in the literature. Zoiset al. (2019a) presented a detailed study of sparse representation techniques for extracting features to verify offline signatures. The extracted features were then fed as an input to binary radial basis SVM classifier for classification purposes. The experiments were conducted on four signature datasets, namely, CEDAR, MCYT-75, GPDS300, and Persian UTSIG dataset, and attained EER of 0.79%, 1.37%, 0.70%, and 6.22%, respectively. The results revealed the superiority of the proposed approach as compared to the state-of-the-art techniques.

4.4 Fuzzy classifier

Zalasiński and Cpałka (2018b) proposed an approach to select a stated number of most significant global features of dynamic signature. The chosen global features were then employed to verify the dynamic signatures based on the fuzzy system. The experiments were carried out on the MCYT-100 signature database and reported a 2.20% average EER which is better in comparison to the one attained by Zalasińskiet al. (2016b). To enhance the efficacy of the dynamic signature verification process, Zalasińskiet al. (2020) presented a new approach in the form of population-based algorithms (PBA) to partition the online signatures. The proposed approach was evaluated using a fuzzy classifier based on the BioSecure DS2 database and attained an average error rate of 3.08% which is better as compared to the ones reported in the previous researches (Cpałka*et al.* 2014a; Cpałka*et al.* 2014b; Cpałkaet al. 2016). Alaeiet al. (2017) proposed writer dependent signature verification method using interval-valued symbolic data to model feature vectors. Then to verify the test sample of signature, the fuzzy similarity measure is employed. The proposed approach is evaluated on two benchmark datasets, namely, GPDS and BHSig260 with an AER of 11.74% on the GPDS-160 dataset. The results revealed that the proposed approach outperforms recent signature verification methods by considering eight or more training samples. An offline signature verification system for bank cheques has been developed by Kumar and Dhandapani (2017). For verifying the signatures, they have combined features like Zernike moments, circularity, and aspect ratio. The extracted features are then given as an input to the fuzzy classifier of the Mamdani type. The results are obtained on a database containing a total of 72 signatures which is further divided into three sets, each set containing 24 signatures. The results reveal that the proposed system achieved an accuracy value of 0.46 on an average.

4.5 Neural network/deep learning based methods

Shariatmadariet al. (2019) proposed writer-dependent approach for signature verification by taking images from the handwritings. This approach employed hierarchical one-class based CNN in order to learn genuine signatures due to the absence of forgeries in real application scenario. The approach is evaluated on two Persian databases (PHBC and UTSig) and two Latin databases (MCYT-75 and CEDAR) and attained better results as compared to state-of-the-art results. Wei et al. (2019) presented Inverse Discriminative Networks (IDN) model to verify writer-independent handwritten signatures. The proposed model comprised four network streams that include two pairs of signature samples. One pair comprises the reference signature sample and test signature sample that aids in extracting the Convolutional features from signatures, whereas the other pair comprises the inverse gray reference signature sample and test signature sample that is centered on signature strokes. This model has been evaluated on a Chinese signature dataset comprising about 29,000 signature samples, and other languages' datasets such as CEDAR, BHSig-B, and BHSig-H with verification accuracies of 90.17%, 95.98%, 95.32%, and 93.04%, respectively. Jain et al. (2020) proposed a shallow Convolutional Neural Network (CNN) approach to verify handwritten signatures. The proposed approach is language-independent that can be applied to signatures of any language. In order to perform experiments, they used various public signature datasets, such as GPDS, MCYT-75, MCYT-100, SVC-2004, and also developed their own two datasets from 137 and 467 individuals, respectively with names CVBLSig-V1 and CVBLSig-V2. To prove this approach as language-independent, they also considered two datasets such as BHSig260 Hindi and BHSig260 Bengali (Pal et al. 2016). The best recognition rate of 99.40% has been attained using the MCYT-100 dataset. The proposed approach attained recognition accuracy of 96.87% using the GPDS-300 dataset, which surpassed the state-of-the-art approaches (Dutta et al. 2016; Dey et al. 2017; Hadjadjiet al. 2017). Whereas on the GPDS-960 dataset, they attained 97.19% accuracy which is superior to existing approaches (Dutta et al. 2016; Dey et al. 2017; Bouamraet al. 2018). OnBHSig260 Hindi and BHSig260 Bengali, the proposed approach attained recognition rates of 97.12% and 98.40%, respectively which are better as compared to existing approaches (Dutta et al. 2016; Pal et al. 2016; Dey et al. 2017). In terms of comparison with other state-of-the-art approaches, they also considered EER. On MCYT-75, they attained 0.4% EER which is better as compared to the existing approaches (Ferrer et al. 2012; Hafemann et al. 2018; Okawa 2018a, 2018b; Zoiset al. 2019b). On MCYT-100, they attained 0.2% EER which proves to be better as compared to existing methods (Manjunathaet al. 2016; Hafemannet al. 2017; Lai et al. 2017; He et al. 2019). Based on the SVC-2004 dataset, an EER of 1.01% has been reported that reveals to be better in comparison to existing approaches (Yeung et al. 2004; Lai et al. 2017; Van et al. 2007; Pascual-Gaspar et al. 2009). They also attained good recognition results of 93.71% and 87.26% on proposed datasets such as CVBLSig-V1 and CVBLSig-V2, respectively.

There are numerous scenarios (e.g., cheque payment in the bank) where the verification of the signature is dependent on the evaluation of a single well-known specimen. In this direction, Kao and Wen (2020) presented a deep CNN approach for offline signature verification and forgery detection dependent on a single known signature specimen. A local feature extraction technique has been incorporated in order to extract the desirable features from the signature specimen. This approach has been evaluated on the ICDAR2011 SigComp dataset (Lewicki et al. 2011), and reported accuracies to lie between 94.37% and 99.96%. The results revealed that even based on a single known sample, the network performance can be successfully enhanced by enlarging the forged specimens. Poddar et al. (2020) proposed a deep learning-based approach for the recognition of offline signatures and forgery detection. The signatures are recognized using CNN and Crest-Trough method, which are then followed by the SURF algorithm & Harris algorithm to detect signature forgeries. For signature recognition and forgery detection, the accuracies of 90–94% and 85–89% have been reported, respectively.Voruguntiet al. (2020) employed Convolutional Autoencoder (CAE) to extract features from online signatures which are then combined with handcrafted features. This hybrid set of features is given as an input to Depth-wise Separable Convolutional Neural Network (DWSCNN). DWSCNN employs less training samples and parameters as compared to traditional CNNs thus leads to lightweight Online Signature Verification (OSV) framework. They evaluated the proposed framework on three public datasets, namely, MCYT-100, SVC-2004-Task2 and SUSIG-Visual corpus. On SUSIG dataset, True Acceptance Rate (TAR) of every user varies between 0.6 and 0.9 and False Acceptance Rate (FAR) varies between 0.2 to 0.5. On MCYT dataset, they attained near 1 TAR and average FAR varies between 0.6 to 0.8. The attained results indicate the superior performance of the proposed framework than state-of-the-art OSV approaches.To the best of their knowledge, the proposed work is the first one that considers hybrid fusion of features and few shots learning.

Ghosh (2021a) proposed Recurrent Neural Network (RNN) based deep learning model for offline signature recognition and verification where numerous structural and directional features are extracted. The extracted features are then given as an input to two distinct models of RNN, namely, long-short term memory (LSTM) and bidirectional long-short term memory (BLSTM) for classification. The proposed model is evaluated on six public signature datasets, namely, GPDS synthetic, GPDS-300, MCYT-75, CEDAR, BHSig260 Hindi, and BHSig260 Bengali and attained average EERs of 2.27%, 1.46%, 0.34%, 0.01%. 0.43% and 0.36%, respectively, using BLSTM. The experiments are also conducted using CNN for purpose of comparison and the results reveal the better performance of the proposed model as compared to CNN and existing state-of-the-art work.Ghosh et al. (2021b) proposed a novel spatio-temporal Siamese Neural Network (ST-SNN) in order to recognize 3D signatures, where the spatial features are extracted by one branch using 1D CNN and the inputs in the temporal domain are processed by the other using Long Short Term Memory networks (LSTMs). Distance Metric is employed that is small for samples from the same individual and large for samples from different individuals. The experiments are conducted on biometric 3D signature benchmark dataset with True Positive Rate (TPR) of 94.63% and False Acceptance Rate (FAR) of 4.1%.Liu et al. (2021) proposed a region based deep metric learning network for offline signature verification based on deep Convolutional Siamese Network. This proposed approach is applicable to both writer-dependent (WD) and writer-independent (WI) scenarios. In order to extract features, Mutual Signature DenseNet (MSDN) is employed. The experiments are conducted on public datasets, namely, CEDAR and GPDS with EERs of 6.74% and 8.24% in WI scenario, respectively and EERs of 1.67% and 1.65% in WD scenario, respectively.

Distance measures

Xia et al. (2018) have proposed a method of discriminative feature selection for on-line signature verification. Signatures were effectively aligned to their reference templates based on Gaussian Mixture Model (GMM) before verification. Then discriminating features are selected among the selected consistent features by two methods of experimental design, i.e., full factorial experiment design (FED) and optimal orthogonal experiment design (OED). According to the FED, discriminative features are considered the main effect factors that can improve the performance of verification. For improving the efficiency of discriminative feature selection, they used the orthogonal experimental design (OED) due to its characteristic of sampling a small number of well representative combinations for the testing set. A modified dynamic time warping with signature curve constraint (DTW with SCC) is proposed for template matching. Comprehensive experiments are implemented on two standard online databases, namely, MCYT_Subcorpus_100 (DB1) and SVC2004 Task2. There are a total of 5900 test signatures from 140 users to be verified. The lowest EER values of 2.17% and 2.60% are provided by the GMM-alignment method implemented on DB1 and SVC2004 Task2, respectively. Parzialeet al. (2019) proposed Stability Modulated Dynamic Time Warping (SM-DTW) algorithm in order to incorporate the stability regions into the distance measure between a pair of signatures calculated by DTW to verify the signatures. A number of features like pen position, pressure, velocity, pressure derivative, and acceleration are considered from each point of the pen-tip trajectory. For evaluation, two datasets, namely, MCYT-100 and BiosecurID-SONOF are considered. On the MCYT-100 dataset, SM-DTW attained its best performance (EER of 3.09%) on skilled forgeries that outperform other baseline systems (Sae-Bae and Memon 2014; Fischer and Plamondon 2017; Guru et al. 2017; Sharma and Sundaram 2017). On the BiosecurID-SONOF dataset, the proposed system attained an EER of 1.45% on skilled forgeries, outperforming other baseline systems (Galballyet al. 2015; Ferrer et al. 2017). Riesen and Schmidt (2019) demonstrated a comparison between two string matching algorithms, namely, Dynamic Time Warping (DTW) and String Edit Distance (SED) in order to verify the signatures. For SED, they adopted a recent cost model (Riesen*et al.* 2016) and the experiments are conducted on three benchmarking datasets, namely, SUSIG-V, MCYT-100 and SIGCOMP-11. Based on experiments, the novel model reduces the mean EERs by 13.8% and 32.8%, using skilled forgeries when compared with DTW and SED, respectively. Thus, the proposed novel cost model in conjunction with SED outperforms both DTW and SED on all the considered datasets.

Multiple Classifiers and Other Approaches.

Zoiset al. (2017) proposed an archetypal analysis-based approach for offline handwritten signature modeling and verification. A set of archetypes is generated as an outcome of the archetypal analysis of few reference specimens, which are utilized to create the foundation of the feature space. Then average pooling yielded the required features to verify offline signatures. The proposed approach is evaluated on two signature datasets, namely, CEDAR and MCYT75 with FRRs of 2.07% and 3.97%, respectively. Due to the diverse writing styles of an individual, multiple unstable fragments exist in the signature. So, to deal with this issue, Dorozet al. (2018) proposed a verification approach for online signatures by focusing on the determination of reference signature stability. The stability measure is based on the fuzzy set theory strategy, which has not been used before to the best of the authors' knowledge. This approach does not require skilled forgeries during the training phase of the classifier. They evaluated the proposed approach on two databases, namely, SVC2004 and MCYT databases using seven classifiers, namely, PSO oriented PNN, k-NN, Naïve Bayes, Random Forest, RIDOR (RIppleDOwn Rule), SVM, and J48. They reported AER (Average Error Rate) of 0.30 and 0.00 using SVC2004 and MCYT databases, respectively, and concluded that the PNN + PSO approach generated the best results out of tested classifiers. In order to eliminate the requirement of numerous samples and pre-trained network weights, Gumusbas and Yildirim (2019) evaluated the performance of capsule network for offline signature identification and verification task.For experiments, they considered CEDAR database and attained accuracies of 98.8% and 98.6% for 64×64 and 32×32 input resolutions, respectively, which surpassed the rates attained via CNN.To obtain significant improvements in verifying signatures, Maergneret al. (2019) proposed an approach to offline signature verification by combining a structural approach based on graph edit distance with a statistical approach based on deep triplet networks. Multiple Classifier System (MCS) is defined for combining the graph-based dissimilarity and neural network-based dissimilarity. They evaluated the proposed approach on four public benchmark datasets, namely, GPDSsynthetic-offline, MCYT-75, UTSig, and CEDAR datasets with EER of 4.76, 3.91, 14.09, and 5.91, respectively (Table 5).

5 Sources of data and signature databases

To conduct the survey, databases are extensively searched which are listed as below and its studies are reported. The most widely used signature datasets are demonstrated in Tables 6, 7 and 8 along with some attributes.

6 Comparison with recent survey works

In this section, the comparison of the presented survey with some of the recent surveys have been provided as elucidated in Table 9. This comparison reveals the superiority of this survey as compared to the existing survey works.

Table 5 Summary of significant signature identification and verification systems

Authors	Dataset	Feature Extraction/ Selection Technique	Classification Technique	Writer Dependent (WD)/Writer Independent (WI)	Results (%)
Guerbaiet al. (2015)	(i) GPDS-300 (ii) CEDAR	Curvelet transformfeatures	OC-SVM	WI	(i) EER: 15.07 (ii) EER: 5.60
Hafemannet al. (2016)	(i) GPDS-160 (ii) Brazilian PUC-PR	Deep CNNfeatures	SVM	WD	(i) EER: 10.70 (ii) EER: 4.17
Hamadene and Chibani (2016)	CEDAR	Directional Code Co-occurrence matrix (DCCM) feature generation method	Feature Dissimilarity Measures (FDM)	WI	EER: 2.55
Soleimani et al. (2016a)	(i) UTSig (ii) GPDSsynthetic (iii) GPDSGraySignature	HOG + DRT	DMML	WI	(i) EER: 17.45 (ii) EER: 13.30 (iii) EER: 22.76
Zoiset al. (2016)	(i) CEDAR, (ii) MCYT (iii) GPDS-300	Operates a family of six groups of grids lattices (GoG's)	SVM	WD	(i) EER: 3.02 (ii) EER: 4.01 (iii) EER: 3.24
Diaz et al. (2017)	(i) GPDS-300 (ii) MCYT-75	Textual features	SVM	WD	(i) EER: 14.58 (ii) EER: 9.12
Okawa (2016a)	CEDAR	KAZE features	SVM	WI	EER: 1.6
Hafemannet al. (2017)	GPDS-160	Deep CNNfeatures	SVM	WD	EER: 1.72
Hafemannet al.(2018)	GPDS	Deep CNNfeatures	SVM	WD	EER: 0.41
Sharif et al. (2018)	CEDAR	Geometrical features + Genetic Algorithm	SVM	WD	AER: 4.67
Bhuniaet al. (2019)	(i) MCYT-75 (ii) CEDAR	Texture features	SVM	WD	(i) EER: 6.10 (ii) EER: 1.64
Gumusbas and Yildirim (2019)	CEDAR	Texture features	Capsule Network	WD	Accuracy: 98.8
Masoudniaet al. (2019)	UT-SIG dataset	Deep CNN features	SVM	WD	EER: 6.17
Zoiset al. (2019a)	(i) CEDAR (ii) MCYT-75 (iii) GPDS300 (iv) Persian UTSIG dataset	Sparse representation techniques	SVM	WD	(i) EER: 0.79 (ii) EER: 1.37 (iii) EER: 0.70 (iv) EER:6.22%
Ghosh (2021a)	(i) GPDS synthetic (ii) GPDS-300 (iii) MCYT-75 (iv) CEDAR (v) BHSig260 Hindi (vi) BHSig260 Bengali	Structural anddirectional features	RNN	WD	(i) EER:2.27 (ii) EER: 1.46 (iii) EER: 0.34 (iv) EER: 0.01 (v) EER: 0.43 (vi) EER: 0.36

Table 6 Signature datasets in Offline Mode

Signature dataset	Signers	Genuine signatures per signer	Forged signatures per signer	Publicly available
Brazilian PUC-PR (Freitas et al. 2000)	168	40	20	No
CEDAR (Kaleraet al. 2004)	55	24	24	Yes
GPDSsynthetic (Vargas et al. 2007)	4000	24	30	No
GPDS960Gray-Signatures (Vargas et al. 2007)	960	24	30	No
BHSig260 (Bangla) (Pal et al. 2016)	100	24	30	Yes
BHSig260 (Hindi) (Pal et al. 2016)	160	24	30	Yes
UTSig (Soleimani et al. 2016b)	115	27	42	Yes
Task SigDutch	27	10	10	Yes
Thai Student Signature (Suwanwiwatet al. 2018)	100	30	24	Yes

Table 7 Signature datasets in Online Mode

Signature dataset	Signers	Genuine signatures per signer	Forged signatures per signer	Publicly available
SVC2004 (Yeung et al. 2004)	100	20	20	Yes
SUSIG-Visual (Kholmatov and Yanikoglu 2008)	100	20	10	Yes
BiosecurID (Fierrez*et al.* 2010)	400	16	12	No
e-BioSign-DS1-Signature (Tolosanaet al. 2017)	65	8	6	Yes
MOBISIG (Antalet al. 2018)	83	45	20	Yes

Table 8 Signature datasets in Offline & Online Modes

Signature dataset	Signers	Genuine signatures per signer	Forged signatures per signer	Publicly available
MCYT (Ortega-Garcia et al. 2003; Fierrez-Aguilar et al. 2004)	330	25	25	Yes
BiosecurID-SONOF (Galballyet al. 2015)	132	16	12	Yes
Task SigJapanese	20	42	36	Yes

7 Implications and future directions

The authors have attempted to survey the existing literature related to signature identification and verification to know the advances in this field. This literature has been surveyed for both online and offline signature acquisition methods. In offline signature verification, a survey related to both writer-dependent (WD) and writer-independent (WI) approaches has been done. The feature extraction techniques have been elaborated with pros and cons. Different existing classification approaches such as Hidden Markov Model (HMM), Support Vector Machine (SVM), template matching, vector quantization, fuzzy approach, Neural Networks, deep learning, hybrid approaches, etc. have been discussed in this survey. Some significant signature identification and verification systems have been summarized in the form of a table for further comparisons. The most widely used signature datasets have also been discussed in this survey paper. Thus, the whole survey is helpful in finding the research gaps in signature identification and verification and highlights the need to develop more robust and more constructive signature identification and verification approaches. So, in the future, the following points can be considered as reference to carry out the research:

- The increase in number of users in the dataset decrease the performance of signature identification and verification systems.
- The increase in the number of samples per user enhances the system performance.
- There is better performance with the utilization of deep learning techniques in extracting the features.
- All the mentioned classifiers can be utilized for both offline and online systems except Dynamic Time Warping (DTW) which can only be employed in online systems.
- Although DTW is considered as a standard procedure for online signature verification, but String Edit Distance (SED) can also be experimented for online signature verification. Careful selection of cost model for SED can lead to better results than employing DTW for online signature verification.
- A hybrid approach can be proposed by combining the different dissimilar models.
- In order to verify the signatures, graphs are rarely used due to the increased computational complexity involved in matching two general graphs. So, one can think of making improvements to the graph matching framework, both in terms of approximation accuracy and computational complexity
- Signature database of people having neurological disorders can be developed apart from the signature of normal people in order to evaluate the performance of signature verification system.

Table 9 Comparison with the recent survey works

Authors	Highlights
Diaz et al. (2019)	A systematic analysis of the past 10 years' state-of-the-art work on handwritten signatures by mentioning the characteristics of the publicly available online and offline signature datasets Demonstrated the most favored algorithms utilized for automatic signature verification Mentioned the performances of some published automatic signature verification systems in distinct scripts Provided a brief description of signature verification competitions conducted in the past 10 years Demonstrated the recent progress in the field of automatic signature verification which provides future directions in the same field
Al-banhawyet al. (2020)	Review on commonly used techniques for pre-processing, feature extraction and classification for online and offline signature identification and verification systems Elaborated performance evaluation metrics for signature identification and signature verification separately Compared the recent proposed techniques for signature identification and verification systems by considering the dataset, extracted features, classifier and evaluation results Revealed the better performance of histogram of oriented gradients technique, SIFT and SURF techniques and mathematical transformation for feature extraction SVM, neural network and deep learning for classification attained promising results
Hameed et al. (2021)	Systematic review of state-of-the-art of Machine Learning based models for offline signature verification systems Demonstrated the review using five parameters, namely, datasets, preprocessing techniques, feature extraction methods, machine learning based verification models and performance evaluation metrics Include research articles between January 2014 and October 2019 Disclosed that deep learning based neural network obtained better results on public datasets Integrated the performance of state-of-the-art offline signature verification systems on five public datasets Open research issues were discussed as per future directions
Jagtap et al. (2021)	Review on offline signature verification by examining the approaches, datasets utilized Discovered the challenges associated with offline signature verification
Stauffer et al. (2021)	Comprehensive overview of the state-of-the-art methods in offline signature verification Provides review of traditional and very recent methods employed in several steps in a generic process of offline signature verification Revealed the great potential for structural signature verification approaches in the future, especially with the rise of deep learning methods for graphs
Present Survey	Systematic overview of online and offline signature identification and verification techniques In offline signature verification, presented surveys related to two approaches, namely, writer-dependent, and writer-independent approaches Introduced several databases in order to evaluate different signature identification and verification techniques and corresponding results are reported in this article General Signature Identification and Verification System has been demonstrated This paper also presents the difference between signature identification and signature verification; between online signature verification and offline signature verification; between writer-dependent (WD) and writer-independent (WI) approaches Moreover, the compiled study of feature extraction and classification techniques used for signature identification and verification process has also been incorporated The signature datasets (online/offline) used in this field have been elaborated Some significant signature identification and verification systems are provided in form of table as per WD / WI approaches Presented synthetic analysis based on literature survey Analyzed the issues and challenges in this field Finally, future directions are provided in order to support the research in the domain of signature identification and verification

Declarations

Conflict of interest Authors declared that they have no conflict of interest in this work.

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